A new minimal path selection algorithm for automatic crack detection on pavement images

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A NEW MINIMAL PATH SELECTION ALGORITHM FOR AUTOMATIC CRACK DETECTION ON PAVEMENT IMAGES

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ABSTRACT

This paper proposes a new algorithm for crack detection based on the selection of minimal paths. It takes account of both photometric and geometric characteristics and requires few information *a priori*. It is validated on synthetic and real images.

***Index Terms*—** Crack detection, minimal path, Dijkstra algorithm, non destructive control, pavement.

1. INTRODUCTION

Monitoring road surface conditions is an important issue in many countries. The objective is to detect surface distresses, like raveling and cracking, in order to plan effective road maintenance and to afford a better sustainability of the pavement structure. Human visual inspection has been gradually replaced by automatic data collection with specific imaging devices [1]. In consequence, processing techniques have been then developed (for monitoring surface conditions) as a support of human visual control [2]. In this paper, only image based techniques are discussed.

The main difficulty for image processing stems from the fact that cracks are particular image features that only appear as thin, irregular dark lines buried into textured noise. Within the scope of automatic crack detection, two kinds of methods can be discussed: unsupervised and supervised [3, 4]. Using a learning machine step [5] provides interesting results but, in this paper, we will work on fully automatic unsupervised techniques.

The methods based only on the photometric information, e.g., threshold methods, are difficult to handle in practice owing to the observed mono modal grey level distribution on the whole images [2, 6, 7]. Conventional contrast enhancement and/or equalization techniques may improve the visual rendering of the image but may also enhance local discontinuities within the crack pattern at the same time, that results in false and incomplete detections. Better performance and robustness against the image texture can be achieved when both photometric and geometric characteristics of cracks are exploited. As an example, mathematical morphological approaches were adopted to reduce the discontinuities (by using dilation operators) within the crack pattern and to remove false detections (by using erosion operators) [8]. But, the automatic implementation of the latter methods is made difficult because of the large amount of parameters to tune. Using filtering methods is a common approach [9] but even when using multiresolution, it is still difficult to have good performance in some cases, e.g., the French pavement images [2, 10]. Some methods introduce local constraints like geometric constraint in a Markovian modeling [2], or both proximity and continuity constraints in a tensor voting approach [11]. However, the constraints at the local scale may counteract the result at the larger scale. Some post-processing, e.g., the minimum spanning tree in [11], is then required to afford the detection of the whole crack network. The most recent approaches introduce a more powerful geometric constraint than previous methods: minimal paths that are supposed to be significantly darker inside the crack than outside the crack.

Using minimal paths has both the advantage of introducing a global photometric constraint and a global geometric constraint. Estimating minimal paths in of each pixel of the image is expensive and, in consequence, the existing approaches have proposed a strategy to reduce this cost. The first possibility is to select small subsets of pixels, based on manual selection [12] or automatic selection of points of interest [13], whereas the second one reduces the estimation of the path by introducing orientation and length constraints [14]. The first approach is too selective and the points of interest detected do not cover all the crack whereas the second approach is not able to detect cracks with fast variations of orientation. For all these reasons, in our previous work [15], we introduced a minimal path approach without any constraints on the orientation nor the length of the paths.

The scope of the proposed algorithm is to select endpoints at the local scale and then to select minimal paths at the global scale. Moreover, the minimal paths are estimated between a subset of pixels that covers all the crack and that is larger than the subset of points of interest used in [13]. The result obtained is a skeleton, i.e. a path with one pixel width in the center of the crack, as illustrated in Fig. 1(d). These results were encouraging but there are still some imperfections, such as: false detections that are assimilating as loops. Moreover, in order to qualify the size of the disorder, it is necessary to detect the width of the crack and this approach can only provide the skeleton. In this paper, we propose an enhanced version in order to cope with such deficiencies and to obtain a result like in Fig. 1(f).

Section 2 presents the proposed minimal path approach. The performance assessment in Section 3 includes a comparison with four other methods which have been processed on both synthetic and real images. Section 4 draws the conclusion and the perspectives.

2. MINIMAL PATH SELECTION

The most famous algorithm to calculate minimal path in graph theory is Dijkstra algorithm [16]. Assuming that the crack pattern can be detected by darker pixels than the image background, a path cost function is defined as the sum of grey levels along the path as follows:

$$C(s,d) = \frac{1}{\text{card}(C)} \sum_{m=s}^{d} I(m), \quad (1)$$

where s is the source point, d the destination point, m is a pixel of the path and card(C) is the length of the path. The crack pattern is assumed to be a series of connected pixels with an arbitrary chaotic shape and length. The authors in [14, 15] consider that the minimal path within a crack reaches a lower cost function than any other path within the image background. The strategy of using this information differs between the two papers. The authors of [14] estimate the minimal path from each pixel of the image with directional constraint (four orientations) and a fixed distance (30 pixels) in order to reduce time execution. The main feature of the approach is to consider that if one orientation gives different grey level distribution than the other orientations, the pixel is probably inside the crack. Consequently, authors select pixels instead of paths, and the connection information given by the estimated selected paths is lost.

As opposed to the latter, [15] proposes to use the information on both cost function and minimal paths throughout the process. Moreover, to reduce time execution, significant pixels are selected as endpoints of the minimal paths. Then, elementary minimal paths are computed at the local level without either direction or length constraints. The histogram of the costs of each path estimated between these endpoints presents a bimodal distribution which allows to choose an appropriate threshold for selecting the best minimal paths, i.e. paths really inside the crack. The first results show how approach manages to detect cracks with chaotic path and orientation changes compared to [14]. However, some defaults have been highlighted: the crack detection contains some loops, cf. Fig. 1(e), and only the skeleton is detected.

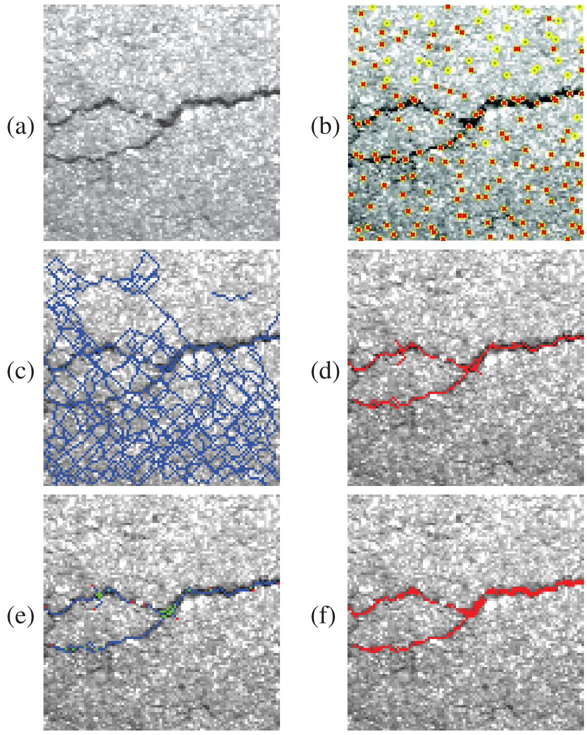

Fig. 1. The five steps from the original image (a) to the result (f) of the MPS method, wich are detailed in section 2.

Here, we propose an enhanced Minimal Path Selection (MPS) algorithm illustrated in Fig. 1, which follows the five following steps:

1. **Automatic endpoints selection, Fig. 1(b):** the best endpoints are selected among the local minima within $P \times P$ sub-images (yellow points in the figure) as the pixels whose the grey level is lower than the threshold $S_a = \mu_a - \sigma_a$, where μ_a and σ_a are the mean and the standard deviation of the whole image, respectively (red points in the figure).

2. **Minimal path computation, Fig. 1(c):** Dijkstra algorithm is used to calculate the minimal paths between the selected endpoints. In this step, there is no constraint on the shape of the paths.

3. **Selection of minimal paths, Fig. 1(d):** Among the large set of paths selected at step 2, only a small subset are within (or partially within) a crack. Here, we use a threshold on the cost function (1) to select the best candidates. The histogram of the costs tends to present two modes contrary to the histogram of the original image. Consequently, we use $S_c = \mu_c - \sigma_c$, where μ_c is the mean and σ_c is the standard deviation of the costs, as a threshold. As shown on Fig 1(d), this step allows to converge to the skeleton of the crack. In fact, when an endpoint is outside the crack, the minimal path al-

gorithm used is able to attract a part of the path inside the crack while the other part is outside. This behavior causes some artifacts: that we call ”spikes” and ”loops”. A spike is a part of path joining a crack to an outer endpoint. A loop is made of two spikes joining at the same endpoint.

4. **Elimination of artifacts (spikes and loops), Fig. 1(e):** With the help of minimal paths estimated, we can detect the outer endpoints and select only the correct parts of the paths, i.e. inside the crack. Local analysis along the crack skeleton is performed to differentiate extremities, e_i: red point, and sources of ramification, s_i: green point. A spike is the path between e_i and s_i and a loop is the path between two s_i. The cost function on each part of the path is studied and it is appropriate to apply the same threshold as step 3 to remove the outer parts of the paths.

5. **Width detection, Fig. 1(f):** The crack skeleton at step 4 allows us to obtain reliable estimation of grey level distribution of the crack pixels. Local analysis is then performed along the crack skeleton which consists of iteratively aggregating the pixels with grey levels below the threshold $S_w = \mu_w + \sigma_w$ where μ_w is the mean and σ_w the standard deviation of the grey levels of the skeleton pixels.

In practice, the proposed algorithm requires four parameters: the thresholds S_a, S_c and S_w at steps 1, 3 and 5 respectively, and the size of the image subsets for local analysis, P at step 1. We choose $P = 8$ because it induces a reasonable computation time (few minutes). The thresholds S_a, S_w and S_c are automatically matched to the statistics of the pixels from the image background (S_a), those from the skeleton cracks (S_w), and the statistics of the cost function (S_c).

3. PERFORMANCE ASSESSMENT

Data Set: To evaluate the performance of MPS we tested the algorithm on a data set of both synthetic and real images from the aigle-RN project :
http://media.lcpc.fr/ext/pdf/sem/2008_jtr_aigle.pdf
The 36 grey level images of size 1920×480 include most of the pavement types under various lightning configurations (with and without controlled lights) and different types of cracks (longitudinal, transverse, alligatoring) with some ramifications at some places.

We generate a new synthetic image which is an improvement compared to [2] where the synthesis of both the crack and the background (i.e., the road surface) is based on a bimodal histogram. Here to be more realistic, an artificial crack pattern is introduced within a real image. The pixels within the crack pattern are randomly generated and the associated grey level distribution obeys the pixel distribution of the real cracks that have been semi-automatically segmented. The width along the crack pattern has been fixed to either one or two pixels. Fig. 2 shows the resulting synthetic image with some ramifications and directional variations.

Pseudo Ground Truth: The assessment of the algorithms can be established with a pseudo ground truth (PGT). In [2], the PGT consists of manually selecting the pixels which were believed to belong to the crack pattern, before merging the individual results from four different operators. We update this PGT by using semi-automatic detection: for each crack piece, two endpoints are manually selected and the crack pattern is estimated with Dijkstra path-finding algorithm [16].

Criterion: The quantitative assessment consists on computing the true positive (TP) (good detection), false positive (FP) (false alarm), and false negative (FN) and calculating the DICE index that is the harmonic mean of precision and sensitivity, which ranges between 0 (worst score) and 1 (best score):

$$DICE = \frac{2TP}{2TP + FP + FN} \tag{2}$$

Methods: As opposed to [13], the performance of the proposed minimal path selection method (MPS) has been compared to three other methods: a **modeling approach** (labelled (M) for Markovian modelling [2]), and two other **minimal path approaches**, namely the Free Form Anisotropy (FFA) by Nguyen [14], and the previous version of the proposed method, labelled (MPS0) [15].

Results and discussion: For both data sets, Markov-based method provides discontinuous crack segmentation owing to the sensitivity to the image texture, see Fig. 2(c) and 4(a). FFA method detects a continuous crack path, but the strategy with directional and length constraints clearly reveals the difficulty to detect the chaotic crack pattern and the fine structure of the crack, e.g., see the change directions and the width on the right of the image Fig. 2(d) and 4(b). MPS0 [13] provides a fair segmentation of the skeleton and the full-length crack, Fig. 2(e) and 4(c). Both loop and spike artifacts have been reduced. Moreover, we can appreciate the width refinement in Fig. 3(f) and 4(d) that is quite precise. In Table 1, among the three methods, Markovian shows the lowest performance, FFA method provides a small improvement in the DICE rate. MPS broadly outperforms the performance of the other methods in any case.

Method	M2	FFA	MPS0	MPS
DICE	0.40	0.46	0.55	0.83

Table 1. Results – DICE values for different methods applied to the synthetic image, see Fig. 2.

At this stage of the development, the drawback of the latter technique is mostly entailed by the computational time encountered by the use of the conventional Dijkstra algorithm. It can be found that the computer time increases a lot beyond $P = 8$, for step 2, and in consequence we choose this

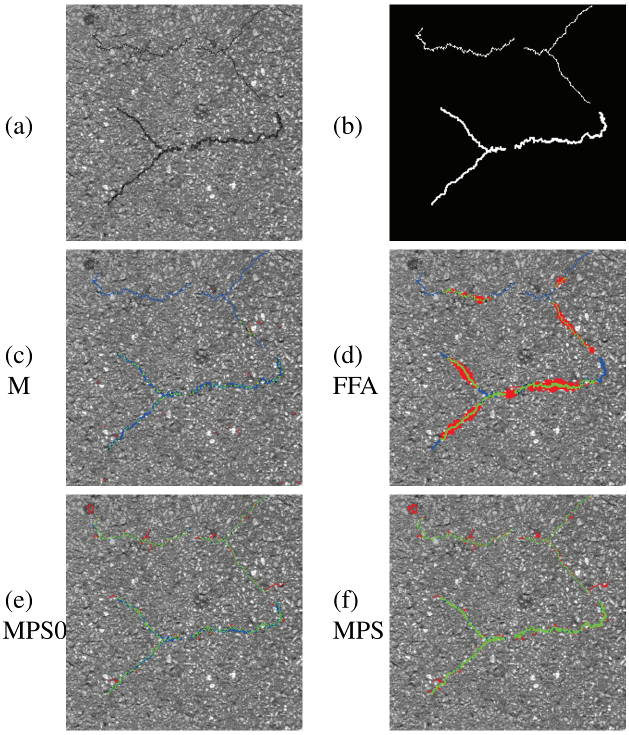

Fig. 2. Results with a synthetic image (a) with ground truth presented in (b). (Green: True Positive, red: False Positive, blue: False Negative).

value. With this parameter, under Matlab programming, the MPS algorithm requires about 12 minutes for the processing of 1MPixels on a 2.7 GHz laptop computer with 8 GB RAM, presented in Fig. 4.

The general quantitative assessment is presented on Fig. 3 for the whole data set of field data. The MPS method gives the highest DICE rate compared to the three other methods; for example, it is twice the score of the markovian method.

4. CONCLUSION

This paper has presented a brief review of existing approaches for the automatic crack detection on pavement images. We introduce an improved version of an algorithm based on minimal path selection by reducing loop and spike artifacts in the crack detection and by adding the width estimation. Pixel-based assessment of the method has shown that the image segmentation is now more reliable than the compared methods. The method allows a very fine characterization of cracks which could be used for further monitoring refinement in the future. In consequence, MPS can detect cracks with variable widths along the skeleton of any form. The future work will focus firstly on testing this method on larger pavement images within the framework of Tomorrow's Road Infrastructure Monitoring & Management (TRIMM) European project

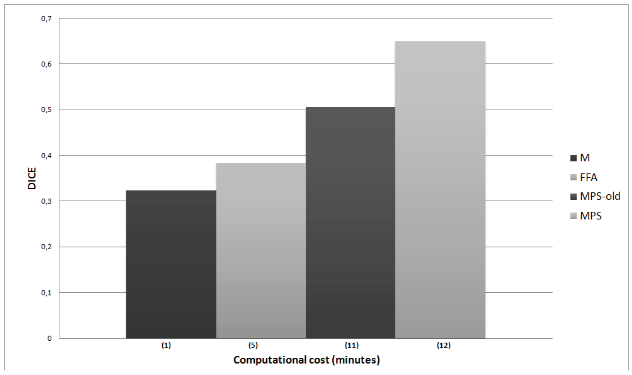

Fig. 3. Mean DICE values versus computational cost (in minutes) obtained by the three methods presented in section 3 and applied on the 36 real images, as an example Fig.4.

(`http://trimm.fehrl.org/`). Secondly, it is also expected to test the MPS approach on 3D data, which are collected with the latest generation of imaging systems, e.g., the LCMS device (`www.pavemetrics.com`) or the RoadScout device (`www.radarportal.com.au`). Thirdly, it is planned to improve the computational efficiency of the second step of MPS (section 2.2) by either GPU programming or using some newer versions of minimal path computation algorithms, e.g., [17].

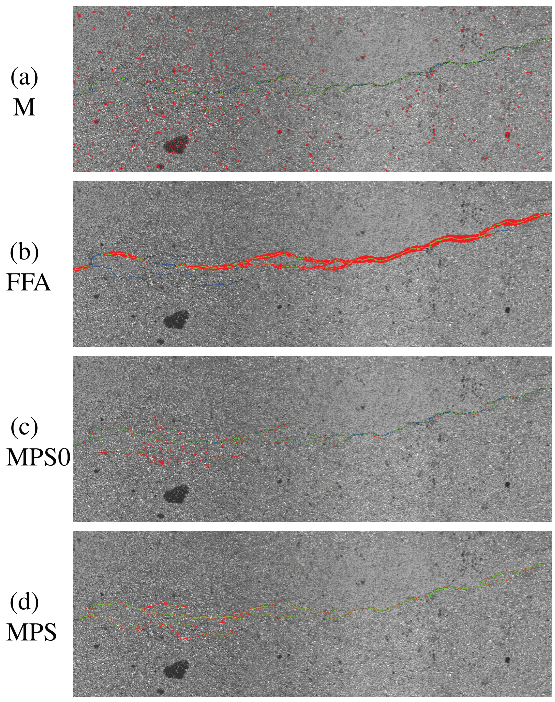

Fig. 4. Results with a real image (Green: True Positive, red: False Positive, blue: False Negative)

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